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Abstract Myoelectric Control with EMG Drive Estimated using Linear, Kurtosis and Bayesian Filtering

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***Abstract*— Three muscle activation estimators: a linear mean-absolute value filter, a recursive Bayesian method, and a kurtosis filter were compared as control approaches for an abstract myoelectric-controlled interface. The linear filter outperformed both the Bayesian and kurtosis methods with respect to participants' overall scores. Despite significantly less efficient trajectories, the Bayesian filter showed a reduction in the time required to reach individual targets. Results demonstrate both that linear methods can outperform more complex filtering techniques, and that real-time kurtosis may be used as an activation estimator.**

I. INTRODUCTION

Artificial limbs, or prostheses, can help individuals perform essential activities of daily living after limb loss or in the case of people born with congenital deficits. The surface electromyogram (sEMG) is a method whereby the electrical manifestation of neuromuscular activity may be recorded in a non-invasive manner. Information generated in the central nervous system may be derived from sEMG and used to control a prosthesis [1]–[3]. Currently, processing of sEMG is the most prevalent method used to control active hand prostheses [4], [5].

In such applications, the sEMG signal is typically transformed into a feature space prior to presentation to a classifier. Features are generally extracted in the time and or frequency domain, a review of methods utilised in the control of hand prosthesis may be found in Micera et al. [6]. The standard feature extraction approaches are based on analysis of the first and second-order moments and cumulants or their representations in the frequency domain. The assumption of such approaches is that the underlying sEMG is a Gaussian process. Higher order statistics (HOS) are useful in problems which must account for non-Gaussianity and nonlinearities [7]. However, the applicability of HOS to EMG is uncertain as no general consensus exists on the shape of the probability distribution function (PDF) of the sEMG signals.

In earlier works, Roesler [8] reported that the Gaussian density function could precisely model experimental EMG obtained from the biceps, triceps and forearm muscles during constant-force, constant-angle, non-fatiguing contractions. Similarly Parker et al. [9] reported that EMG obtained using fine wire intramuscular electrodes during both light and moderate contraction of the biceps may be modelled as a Gaussian process. Recording isometric, constant-force nonfatiguing contractions from the biceps, Hunter et al. [10] found the EMG PDF to deviate from the Gaussian, having a more pronounced sharp peak. Bilodeau et al. [11] recorded EMG during non-fatiguing constant-angle contractions of the biceps using both constant-force and varying force and found distributions to be peaked and non-Gaussian.

Whether a Gaussian or a Laplace density best describes EMG obtained from constant-angle, constant-force, nonfatiguing contractions was addressed by Clancy and Hogan [12], who found densities to fall between the two distributions, with the Gaussian providing the better overall fit. Sanger examined the PDF of activity recorded from bicep and triceps at differing contraction levels and found the Laplace distribution to be more suitable for modelling EMG at low contraction levels [13]. Likewise, previous work from our lab based on the same muscles found the Laplacian distribution to provide a better fit at lower contraction levels [14]. Numerous studies report more Gaussian distributed signals as contraction level increases [10]–[12], [15], with more recent Negentropy analysis [16], [17] confirming that the degree to which an EMG distribution resembles the Gaussian is dependent on muscular contraction level.

The PDF informs the choice of maximum likelihood estimator (MLE) for measuring EMG amplitude. In a prostheses context amplitude maybe used as a proxy for desired force. In this paper we present preliminary work comparing three signal processing techniques for myoeletric control. Active prostheses typically rely on low level EMG contraction, we therefore test filters compatible with a Laplacian distribution. We compare use of mean-absolute-value (MAV) against a Bayesian estimate of the EMGs 'neural drive' and sequentially updated Kurtosis. Tests were performed while participants learned to control a myoelectric-controlled interface (MCI) which acts as an established framework within which to study control mechanisms relevant to prosthesis use [18].

The MAV estimator is the MLE for the Laplacian model [12] and a standard sEMG processing technique. The Bayesian filtering method tested was developed by Sanger [13]. Sanger's method assumes a half-Laplacian exponential density for the rectified sEMG signal and models neural drive as a combined jump and diffusion process. We have used the Bayesian method in previous myoelectric-control work [18] and a modified alternative has recently been evaluated in an online proportional control experiment [19]. Recent work has shown that Kurtosis may be used as a measure of contraction force [15], [17], [20], which may be more discriminative than amplitude at lower levels of contraction [15].

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II. METHODS

A. Participants

Ten participants took part in this experiment (6 male and 4 female). All were able-bodied and free from motor or neurological disorder. Approval was granted by the local ethics committee at Newcastle University. All participants gave informed written consent before participation.

B. Experimental Setup

Participants sat in experimental chair with their right hand restrained in a pronated open position within a glove. The fingers and palm of the glove were fixed to a board and the board was attached to the armrest of the experimental chair. EMG was recorded from the abductor pollicis brevis (APB) and the abductor digiti minimi (ADM). Measurements were obtained using disposable snap electrodes (Nicolet® reusable leads, Care Fusion, Middleton, WI, USA. Bio-logic® press-stud electrodes, Natus Medical Inc, San Carlos, CA, USA). Myoelectric signals were amplified with a gain of 5 K (D360 Amplifier, Digitimer, Hertfordshire, UK) and band-pass filtered between 30 Hz and 1 kHz. A data acquisition card (NI USB-6212 BNC, National Instruments, Austin, TX, USA) digitised signals at a 5 kHz sampling rate.

A calibration routine was performed prior to each experiment which matched that outlined in [18]. Data representing resting level, y_r, comfortable contraction level, y_c, and measurement offsets for both EMG channels were obtained. Participants were instructed to contract muscles in a manner that could be comfortably maintained and repeated without fatigue. In similar previous studies this corresponded to an activity level between 10-20% of the maximum voluntary contraction [21], [22]. A normalized muscle activation level, $\breve{y} = (y - y_r)/(y_c - y_r)$, corresponding to the output of each filter applied to raw EMG measurements, y, was used during experiments.

C. Experimental Protocol

The experimental protocol broadly follows that described in [23]. Participants used isometric muscle co-contraction to operate an abstract MCI. The position of a 2-D cursor was determined according to the activity of each muscle, as outlined in Figure 1. The MCI was calibrated such that normalized muscle activation, $\breve{y} \approx 1$, would bring the cursor to the edge of the interface. The right side of Figure 1 shows a cursor trajectory for an individual trial. At the start of the trial the cursor and the basket at the base of the interface were presented. For a trial to commence participants had to remain in a relaxed state within the basket.

Trials were 1.5 seconds long and composed of two 750 ms periods. The first 750 ms was used for moving the cursor from the basket to the target. Participants were instructed to attempt to retain the cursor within the target area during the second 750 ms, denoted the 'hold period'. The degree to which the target was within, or in contact with, the target during the hold period was used to calculated a percent hold score. The percent hold score was presented to the participant after each trial. Participants performed four blocks of 72 trials for each EMG filtering method. The order in which filters were tested was counter balanced across participants.

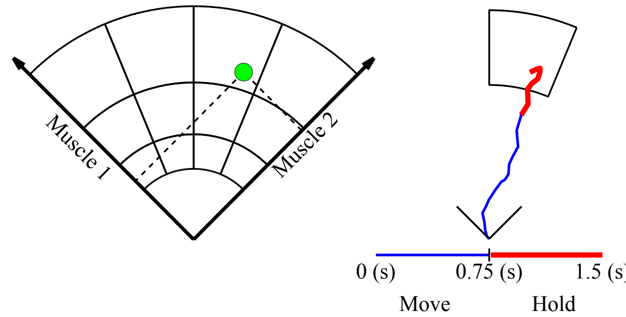

Fig. 1: The 2-dimensional MCI space and a representative cursor trajectory. Blue and red traces show cursor trajectory during trial movement and hold periods respectively.

D. Muscle Activation Estimators

1) Linear Filter: The linear, or mean absolute value, filter averaged the rectified EMG signal over a 750 ms window. Output was updated continuously such that any change in EMG amplitude was reflected in the proceeding update step.

2) Bayesian Estimator: The Bayesian estimator is a recursive algorithm which updates the posterior probability density of a supposed 'neural drive' with each updated EMG sample [13]. The neural drive is modelled as a combined jump and diffusion process, and the rectified EMG as a random process with exponential density. As in previous applications of the filter EMG was clipped at ± 3 standard deviations to avoid modelling extreme values. [13], [18]

3) Kurtosis Estimator: Kurtosis was calculated based on one pass methods for the calculation of statistical moments [24], [25]. For data set $\mathscr{S}_1$ of size $n-1$ and mean μ_1, the updated mean μ of data $\mathscr{S} = \mathscr{S}_1 \cup \{y\}$ and succeeding statistical moments of data $\mathscr{S}$ were calculated as:

$$\mu = \mu_1 + \frac{y - \mu_1}{n} \tag{1}$$

$$M_{2,\mathscr{S}} = M_{2,\mathscr{S}_1} + (y - \mu_1)(y - \mu) \tag{2}$$

$$\begin{aligned} M_{3,\mathscr{S}} = M_{3,\mathscr{S}_1} + (y - \mu_1)(y - \mu)\frac{y - \mu_1}{n}(n-2) \\ -3\frac{y - \mu_1}{n} M_{2,\mathscr{S}_1} \end{aligned} \tag{3}$$

$$\begin{aligned} M_{4,\mathscr{S}} = M_{4,\mathscr{S}_1} + (y - \mu_1)(y - \mu)\left(\frac{y - \mu_1}{n}\right)^2 \\ (n^2 - 3n + 3) + 6\left(\frac{y - \mu_1}{n}\right)^2 M_{2,\mathscr{S}_1} \\ -4\frac{y - \mu_1}{n} M_{3,\mathscr{S}_1}. \end{aligned} \tag{4}$$

A 750 ms window was used as a FIFO buffer for calculation of statistical moments. The inverse of (1) to (4) were applied to samples as they were dequeued from the buffer.

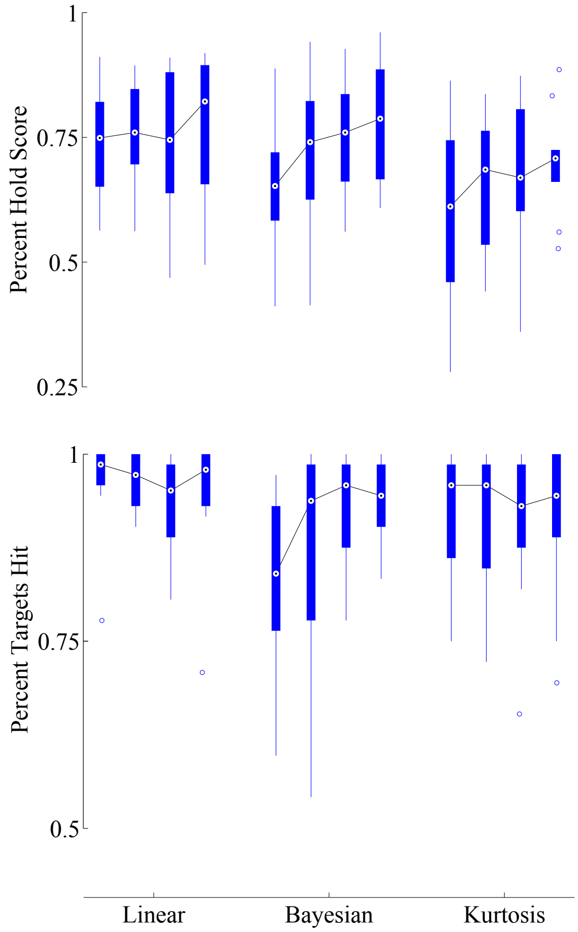

Fig. 2: Performance over runs for each filter. Linked circles show medians and boxes the first and third quartile. Upper plot shows percent hold score presented as feedback. Lower plot shows the percentage of targets hit by participants.

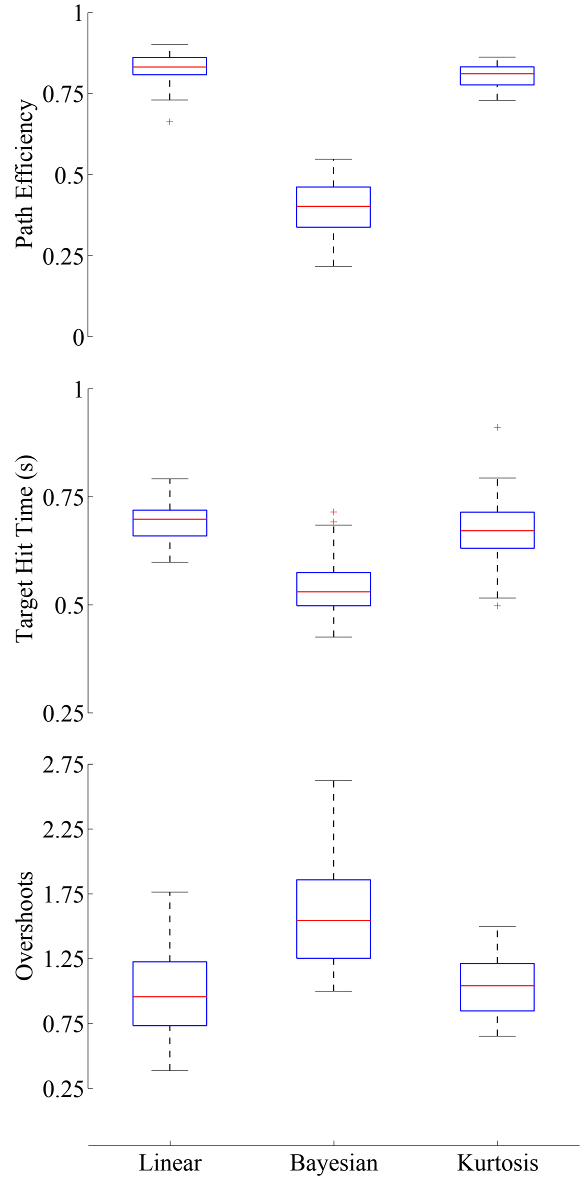

Fig. 3: Box plots of showing pertinent differences between filters. Upper row shows path efficiency, middle row shows target hit time, lower row shows number of overshoots.

III. RESULTS

The upper part of Figure 2 shows percent hold scores, as presented to participants during experiments. Scores for the Linear filter were significantly higher, $Mdn = 0.789$, than those of the Kurtosis filter, $Mdn = 0.663$ (Wilcoxon Signed-Ranks Test, $Z = 2.3953$, $p < 0.05$). The percentage of targets hit over runs are shown in the lower part of Figure 2. Hit rates were significantly higher for the Linear filter, $Mdn = 0.979$, than both the Bayesian, $Mdn = 0.912$, (Wilcoxon Signed-Ranks Test, $Z = 2.3969$, $p < 0.05$) and Kurtosis, $Mdn = 0.934$, (Wilcoxon Signed-Ranks Test, $Z = 2.4479$, $p < 0.05$) filters.

Figure 3 shows path efficiency (top), target hit time (middle) and overshoots (bottom) for each of the filtering methods. Path efficiency was calculated by dividing the optimal trial trajectory to reach the target over the trajectory taken. Path efficiency for the Bayesian filter was significantly lower, $Mdn = 0.402$, than that of the linear filter, $Mdn = 0.832$, and the Kurtosis filter, $Mdn = 0.811$ (Wilcoxon Signed-Ranks Test, $Z = 2.8031$, $p < 0.01$). No significant differences were observed in path efficiency between the Linear and Kurtosis filters.

Target hit time was significantly lower for the Bayesian filter, $Mdn = 0.530$, than both the Linear, $Mdn = 0.698$, and Kurtosis, $Mdn = 0.672$, filters (Wilcoxon Signed-Ranks Test, $Z = 2.8031$, $p < 0.01$). Hit time for the Linear and Kurtosis filters did not differ significantly. Overshoots were defined as the number of time the cursor left the target after having been in contact with it. The number of overshoots using the Bayesian filter was significantly higher, $Mdn = 1.546$, than for the Linear, $Mdn = 0.958$, and Kurtosis, $Mdn = 1.042$, filters (Wilcoxon Signed-Ranks Test, $Z = -2.8031$, $p < 0.01$). No significant differences were found in the rate of overshoots using the Linear and Kurtosis filters.

IV. CONCLUDING REMARKS

The Linear filter outperformed the Kurtosis based method and produced similar percent hold rates to the Bayesian method tested. Rates of improvement in percent hold score were more apparent in the Bayesian and Kurtosis filters, while improvement in target hit rate was largely restricted to the Bayesian filter. Hit rate differences may be attributable to the Kurtosis and Linear methods being sufficiently similar for participants to generalise between the two, whereas optimal co-contraction behaviour for the Bayesian filter is likely to be different as is the rate at which the cursor moves.

A number of the participants tested in this data set were not naive to MCI use. This makes generalisation from the results presented difficult as rates of performance do not plateaux for any method tested. Results may therefore be biased toward the Linear filter because, as the least specialized of the filtering methods, participants are more likely to have experienced this estimator previously. This would explain the lack of learning effects observed for the Linear filter, which were apparent over initial runs for the alternative filters.

In contrast to the Bayesian method used by Hofmann et al. [19] the Sanger filter produced significantly reduced path efficiency and significantly increased rates of overshooting in comparison to the Linear and Kurtosis methods. Both path efficiency and overshoots were probably affected by the Bayesian filter [13] exceeding its position when transitioning between contraction levels, an issue Hofmann et al. recently addressed with an updated method. Akin to Hofmann et al. the time required to reach targets was significantly reduced when using the Bayesian filter suggesting a higher information transfer rate may be achieved using this approach.

More robust alternatives to the standard measure of kurtosis have recently been proposed for EMG processing, namely L-kurtosis [26] and quantile based approaches [27]. Both methods address sensitivities introduced in the standard kurtosis calculations when raising data to higher powers. We intend to include these filters and the modified Bayesian method described in [19] in ongoing tests of muscle estimators for myoelectric-control.

Based on the current snapshot of results we may conclude the following. During early MCI use, simple linear methods may provide better overall performance than more complex techniques. Higher order statistical methods can be used to extract a viable control signal from EMG in real time. Of the methods tested the Bayesian approach provides a significantly more responsive estimate of online EMG activity.

REFERENCES

[1] G. Hefftner and G. Jaros, "The electromyogram EMG as a control signal for functional neuromuscular stimulation-part ii: practical demonstration of the emg signature discrimination system," *IEEE Trans Biomed Eng.*, vol. 35, no. 4, pp. 238–242, 1988.

[2] E. Park and S. G. Meek, "Adaptive filtering of the electromyographic signal for prosthetic control and force estimation," *IEEE Trans Biomed Eng.*, vol. 42, no. 10, pp. 1048–1052, 1995.

[3] Y. Huang, K. B. Englehart, B. Hudgins, and A. D. Chan, "A Gaussian mixture model based classification scheme for myoelectric control of powered upper limb prostheses," *IEEE Trans Biomed Eng.*, vol. 52, no. 11, pp. 1801–1811, 2005.

[4] M. Zecca, S. Micera, M. C. Carrozza, and P. Dario, "Control of multifunctional prosthetic hands by processing the electromyographic signal," *Crit Rev Biomed Eng*, vol. 30, no. 4-6, pp. 459–485, 2002.

[5] M. A. Oskoei and H. Hu, "Myoelectric control systems - a survey," *Biomed Signal Process Control*, vol. 4, no. 2, pp. 275–294, 2007.

[6] S. Micera, J. Carpaneto, and S. Raspopovic, "Control of hand prostheses using peripheral information," *IEEE Rev Biomed Eng.*, vol. 3, pp. 48–68, 2010.

[7] J. M. Mendel, "Tutorial on higher-order statistics (spectra) in signal processing and systems theory: theoretical results and some applications," *Proc. IEEE*, vol. 9, no. 3, pp. 278–305, 1991.

[8] H. Roesler, *The control of upper-extremity prostheses and orthoses*. Springfield, IL: Thomas, 1974.

[9] P. Parker, J. Stuller, and R. Scott, "Signal processing for the multistate myoelectric channel," *Proceedings of the IEEE*, vol. 65, no. 5, p. 662674, 1977.

[10] I. W. Hunter, R. E. Kearney, and L. A. Jones, "Estimation of the conduction velocity of muscle action potentials using phase and impulse response function techniques," *Med Biol Eng Comput.*, vol. 25, no. 2, pp. 121–126, 1987.

[11] M. Bilodeau, M. Cincera, A. Arsenault, and D. Gravel, "Normality and stationarity of EMG signals of elbow flexor muscles during ramp and step isometric contractions," *J Electromyogr Kinesiol.*, vol. 7, no. 2, pp. 87–96, 1997.

[12] E. A. Clancy and N. Hogan, "Probability density of the surface electromyogram and its relation to amplitude detectors," *IEEE Trans. Biomed. Eng.*, vol. 46, no. 6, pp. 730–739, 1999.

[13] T. D. Sanger, "Bayesian filtering of myoelectric signals," *J. Neurophysiol.*, vol. 97, no. 2, pp. 1839–1845, 2007.

[14] K. Nazarpour, A. Sharafat, and S. Firoozabadi, "Application of higher order statistics to surface electromyogram signal," *IEEE Trans Biomed Eng.*, vol. 40, no. 10, pp. 1762–1769, 2007.

[15] K. Nazarpour, A. H. Al-Timemy, G. Bugmann, and A. Jackson, "A note on the probability function of the surface electromyogram signal," *Brain Res. Bull.*, vol. 90, pp. 88–91, 2013.

[16] K. Nazarpour, A. Sharafat, and S. Firoozabadi, "Negentropy analysis of surface electromyogram signal," in *Proc. IEEE Statistical Signal Processing Workshop*, Bordeaux, France, July 2005, pp. 974–977.

[17] G. Naik, D. K. Kumar, and S. P. Arjunan, "Kurtosis and negentropy investigation of Myo electric signals during different MVCs," in *Proc. ISSNIP Biosignals and Biorobotics Conference (BRC)*, Santo Vitoria, Brazil, Jan 2011, pp. 40–44.

[18] T. Pistohl, C. Cipriani, A. Jackson, and K. Nazarpour, "Abstract and proportional myoelectric control for multi-fingered hand prostheses," *Ann Biomed Eng.*, vol. 41, no. 12, pp. 2687–2698, 2013.

[19] D. Hofmann, N. Jiang, I. Vujaklija, and D. Farina, "Bayesian filtering of surface emg for accurate simultaneous and proportional prosthetic control," *IEEE Trans Neural Syst Rehabil Eng.*, vol. 24, pp. 1333–1341, 2015.

[20] S. Thongpanja, A. Phinyomark, C. Limsakul, and P. Phukpattaranont, "Probability density of electromyography signal for different levels of contraction of biceps brachii," in *Proc. 10th Int. ECTI-CON*, Krabi, Thailand, May 2013, pp. 1–5.

[21] K. Nazarpour, A. Barnard, and A. Jackson, "Flexible cortical control of task-specific muscle synergies," *J. Neurosci.*, vol. 32, no. 36, pp. 12 349–12 360, 2012.

[22] T. Pistohl, D. Josh, G. Ganesh, A. Jackson, and K. Nazarpour, "Artificial proprioceptive feedback for myoelectric control," *IEEE Trans Neural Syst Rehabil Eng.*, vol. 23, no. 3, pp. 498–207, 2015.

[23] J. Barnes, M. Dyson, and K. Nazarpour, "Comparison of hand and forearm muscle pairs in controlling of a novel myoelectric interface," in *Proc. IEEE Conf. Syst., Man, Cybern.*, Budapest, Hungary, October 2016, pp. 2846–2849.

[24] T. B. Terriberry. (2008, Oct) Computing higher-order moments online. [Online]. Available: https://people.xiph.org/~tterribe/notes/homs.html

[25] P. Pébay, "Formulas for robust, one-pass parallel computation of covariances and arbitrary-order statistical moments," Sandia National Laboratories, Livermore, CA, Tech. Rep. SAND2008-6212, 2008.

[26] S. Thongpanja, A. Phinyomark, C. Limsakul, and P. Phukpattaranont, "Analysis of electromyography in dynamic hand motions using l-kurtosis," *Appl Mech Mater*, vol. 781, pp. 604–607, 2015.

[27] S. Thongpanja, A. Phinyomark, F. Quaine, Y. Laurillau, C. Limsakul, and P. Phukpattaranont, "Probability density functions of statationary surface EMG signals in noisy environments," *IEEE Trans. Instrum. Meas.*, vol. 65, no. 7, pp. 1547–1557, 2016.